Harveri : A Small (Semi-)Autonomous Precision Tree Harvester

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***Abstract*— This article presents the development of a small harvester (Harveri) targeted for thinning operations and energy tree harvesting. We are interested in two possible use cases: teleoperation by a human and fully autonomous operation. We introduce Harveri itself, together with the hardware modifications made to facilitate the automation of the machine. Furthermore, we describe the sensors used and the rationale behind each sensor choice and physical placement on the machine. The article also discusses computation units used to achieve the teleoperation and autonomy task and connectivity to the machine. Most of the autonomy features are ported from our previous work on HEAP, and in this article, we describe the modifications necessary for Harveri. We present the current automation progress and give directions for future work.**

I. INTRODUCTION

Forests cover about 30% of the world's land surface and are crucial allies in humanity's attempt to fight climate change. Nowadays, forestry is undergoing a paradigm shift, and practitioners are moving away from traditional forestry practices (e.g., compartment-based management) that were described in [1]. With the coming of the digital age, decisions are being made on a much more granular level with the aid of massive data, and machine intelligence [2]; the commercialization of this technology has already begun [3], [4]. However, the robotic community has tackled chiefly the problem of building a forest inventory with minimal attempts to interact with the forest environment. There is a clear research gap for forestry machines interacting with trees. This work focuses on developing a small-scale harvester and the autonomy modules required for a thinning mission. Thus we attempt to bring the forest machines one step closer to uncrewed operation.

Automation of our harvester (Harveri) is broken down into two steps. In the first step, we enable teleoperation on the machine with some autonomy features (e.g., automatic tree trunk grasping). Teleoperation capabilities allow machine commercialization until the autonomy pack is ready. Furthermore, teleoperation helps solve the labor shortage problem since machine operators can operate multiple machines from the comfort of their homes. In the second step, a fully autonomous Harveri will be deployed.

A. Related Work

Autonomous operation with Harveri is largely based on our previous work [5], [6], [7], [8]. A comprehensive overview of scientific publications relevant for forestry robotics is presented in [5]. To the best of our knowledge, apart from Hydraulic Excavator for an Autonomous Purpose (HEAP) presented in our previous work [5], no autonomous (or teleoperated) system for autonomous tree harvesting exists. The interested reader is referred to [5] for more details. Apart from our work, [9] present some preliminary results for forestry automation with Bobacat T190. We have been able to find a company attempting to automate tree harvesting [10]; however, we found no relevant publications about their approach.

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Fig. 1. Harveri harvester parked on our testing field. Automating the machine is currently a work in progress.

Tele-operation capabilities have been demonstrated on HEAP in our previous work. This included teleoperation over 5G networks [11], cleaning up a rock slide [12] and cleaning up an ammunition contaminated environment [13]. We would use the same technology on Harveri.

II. HARDWARE MODULES

This section presents the harvester and the essential hardware components used for automation.

A. Harvester

The tree harvester used in this work is Harveri manufactured by Oy RCM Harvester LTD. It is a small, radio-controlled harvester intended mainly for first thinning and energy wood harvesting since the maximal harvesting diameter is 30 cm. Harveri can negotiate tight spaces between the trees and leave minimal damage to the forest floor. The basic information about the machine is shown in Tab. I.

Harveri has two hydraulic circuits: one for driving the machine (drive hydraulics) and one for boom movements,

(a) Rear laser (b) Front laser (c) Main camera and laser

Fig. 2. Sensor placement on Harveri. In total, we use three lasers and three cameras (only 1 shown). Note that main camera and the laser shown in Fig. 2c rotate together with the arm, thus always keeping the harvesting tool within the FOV.

TABLE I
HARVERI CHARACTERISTICS

weight	4500 kg	transport height	2.81 m
length	4.22 m	wheelbase	1.60 m
width	2.20 m	turning radius	8.75 m
propulsion	hydrostatic	payload	1500 kg

harvester functions, and chassis balancing (working hydraulics). In our version of the harvester, we replaced the chassis hydraulic circuit and installed 4 Moog valve blocks; the same ones as in our previous work [6], [7]. The Moog valve blocks are shown in Fig. 3, and their primary function is to achieve terrain adaptation through precise contact point force control. The valve blocks are equipped with direct drive servo valves, pressure sensors, and Integrated Control Modules (ICMs). The ICMs are running cylinder control loops directly on a micro-controller.

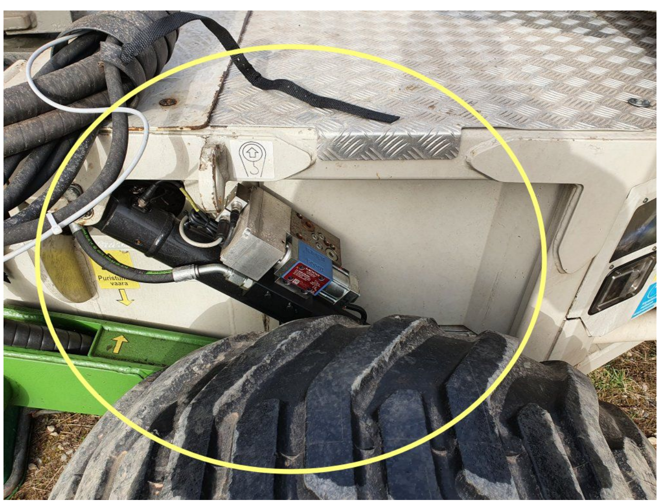

Fig. 3. Moog valve block with an ICM. The new actuators are mounted on the HFE joints to enable accurate and responsive chassis balancing.

B. Sensors

The machine is equipped with proprioceptive, visual, and laser sensors. SBG Ellipse-A Inertial Measurement Unit (IMU) provides roll and pitch for the chassis (see [14]). Similar to our previous work [5], we use inertial sensors to estimate the End-Effector (EE) position. Inertial sensors avoid entanglement problems that could arise from using the draw-wire sensors in a forest environment. Three Aceinna IMUs are mounted on the boom links [15] to estimate the EE position except for the arm telescopic joint where a draw-wire sensor could be mounted inside the link and thus protected from the environment (see Fig. 4). We chose all IMUs sensor characteristics to match the ones we have on HEAP since HEAP sensors worked well for a wide range of applications (see [6]). A Hall sensor is mounted on the middle hinge of the machine to measure the steering angle accurately [16]. Lastly, a Hall sensor (or rotary encoder) will be mounted to measure the arm's turn (slew) angle.

Fig. 4. Mounting location of proprioceptive sensors. Inertial sensors are shown in red and the encoder in turquoise color. Note that the IMU sensors are mounted as close as possible to the joint axis to minimize the inertial forces measured by the sensor.

We use three laser sensors for mapping, localization, and enhancement of the operator's view with 3D information. Multiple smaller laser sensors (as opposed to one sensor with many channels) were chosen to provide redundancy in case of occlusion. Two Velodyne Puck sensors are mounted on the opposite ends of the machine and enclosed in a rugged steel cage. We chose the sensor placement to provide large

FOV which is beneficial for localization. Furthermore, one Hesai QT 64 laser sensor is mounted close to the arm. It was chosen for its sizeable FOV of 104.2 degrees which helps make local maps used for grasp pose planning (see [5] for details). Besides providing redundancy for localization, Hesai's overlapping FOV with the camera enables us to enhance the operator view with 3D information. Mounting locations of all three LIDARs and the camera are shown in Fig. 2. Sensor placement was done purely heuristically.

Harveri is also equipped with three Ximea MC031CG-SY cameras with 4.5 mm lenses to stream images to the operator. The lens focal length was chosen heuristically such that the tool is of appropriate size in the image. The camera model was chosen based on our previous experience on HEAP and because our image processing software is tied to the Ximea cameras. Visual sensors shall also aid in visual navigation and/or traversability estimation in the future. The crane view camera is positioned such that the tool and the end effector are always centralized in the image. Its position can be seen in Fig. 2c. Note that the camera rotates together with the boom, thus enabling the operator always to have the harvesting tool in FOV. For now, only the crane view camera is mounted on Harveri.

The sensor positions are not final and will be refined as more testing is done on the machine. Once the sensor locations on the machine are finalized, we intend to design rugged enclosures to protect the hardware from the elements and tree debris.

C. Computation & Connectivity

Harveri has two computing units. A Programmable Logic Controller (PLC), which communicates directly to the hydraulic valves over Controller Area Network (CAN) (except the Moog valves), and an embedded PC which is connected to the Moog valves and all the sensors. The embedded PC is Neousys Nuvo-8108GC with Intel i7-9700E CPU, 32 GB of working memory, and NVIDIA GeForce RTX 2060 GPU. The computationally capable GPU encodes and compresses video streams from the cameras and runs different algorithms required for autonomous operation (e.g., segmentation, fast scan registration, etc.). An important factor in choosing the appropriate GPU is the number of hardware encoders for video streams. We decided on the Neousys PC for passive cooling and casing with vibration damping. A suitable PC case becomes important since dust may clog the CPU fans, and engine vibrations damage the components. The computing power is most likely over-dimensioned; however, we don't know yet what kind of algorithms we will exactly need.

The software is developed primarily in the C++ programming language, and we commnicate between the processe using both ROS 1 and ROS 2 (mainly for communication with the Augmented Reality (AR) layer). The main control loop runs at 100 Hz. Since ROS is language agnostic, it is easy to add new modules in other programming languages (e.g., Python) if the autonomy module requires it.

Tele-operation requires a high bandwidth internet connection which may not be available in all scenarios. Previously, we used a 4G or 5G network to stream the images over the network. The deployed custom image compression allows us to operate well within a typical 4G network bandwidth (assuming no heavy congestion from the other users). Together with our project partner [3] and local network carriers, we conducted initial bandwidth tests, which showed that Harveri teleoperation over a 4G network would be possible in many areas of interest. However, to accommodate use cases in all the forests, one would have to look into different solutions such as mobile base stations, local meshing, or breadcrumb network nodes.

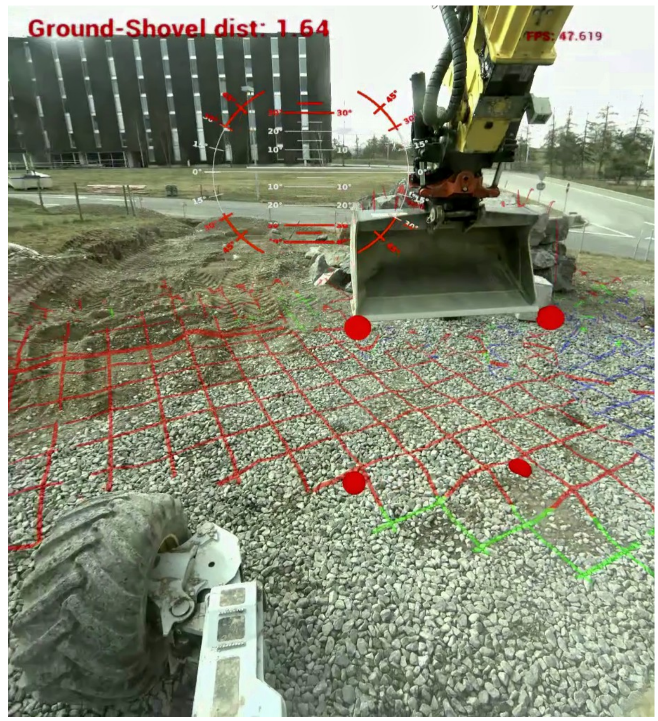

Fig. 5. AR elements overlaid on top of the image stream. In this example, the user was digging with HEAP and relying on the image stream. Bold red circles in Fig. 5 show the shovel corners and their vertical projection on the ground to regain the lost depth perception in a 2D image. Furthermore, the operator is provided with the ground-shovel distance in numerical format. In this example, the green color denotes the desired height, whereas the red color means that the operator should remove material and deposit it in the blue-colored areas. Lastly, the operator is presented with a dial similar to the artificial horizon used in aviation. The red numbers in the dial denote unstable regions where the machine is in danger of tipping over.

III. TELEOPERATION & AUTONOMY MODULES

In this section, we present AR elements used to enhance the image stream for the operator together with the autonomy modules ported from [5] to Harveri.

A. Teleoperation AR elements

Operator view with the AR elements overlaid on top of the camera stream is shown in Fig. 5. In this case HEAP was teleoperated. We take the elevation map [17] that is built online from the laser sensors and project it in the image to display the ground height information. The rest of the AR

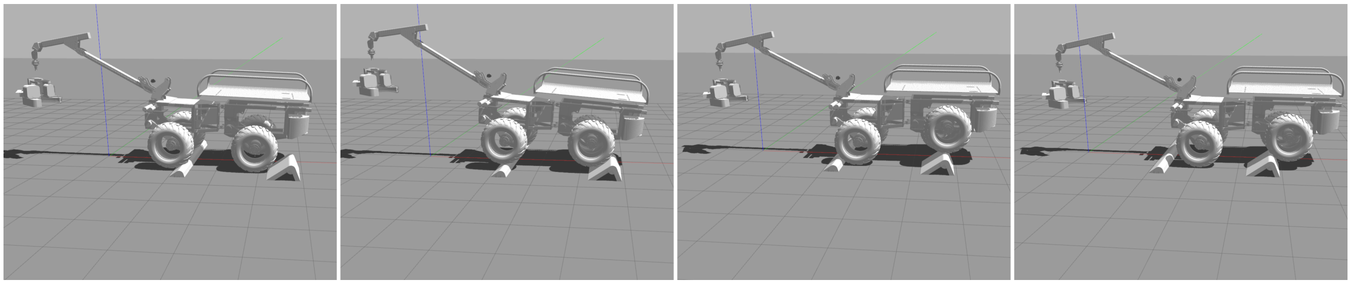

Fig. 6. *Left to Right:* Harveri overcoming irregular terrain in Gazebo simulator. Note how the left hind wheel retracts to keep the chassis leveled.

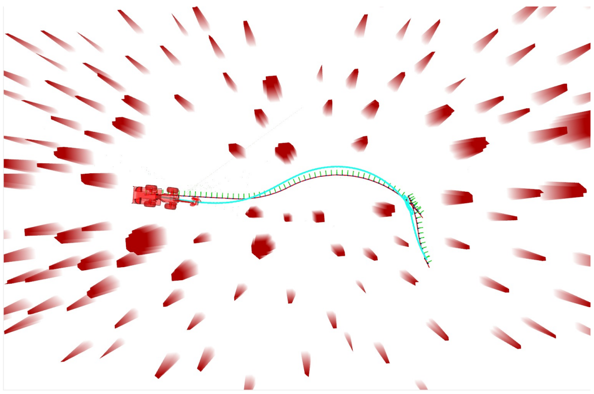

Fig. 7. Harveri tracking a planned path; each pose on the path is denoted with coordinate axes (x-axis in red, y in green, z in blue). The obstacles are shown in red color and free space in white. The tracked path is shown in cyan color. The machine itself is shown in red.

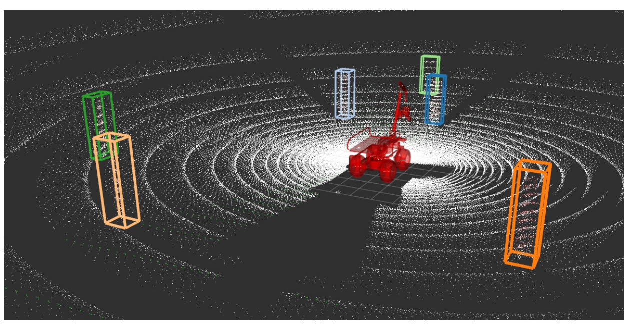

Fig. 8. Harveri detecting simulated trees (marked with bounding boxes) after performing a scanning maneuver in simulation.

elements is computed by projecting kinematic information into the image. For use on Harveri, we intend to modify some of the AR cues. The current software stack will be extended with real-time tree detection (either from images or from local maps assembled with the laser scanner), and the trees will be marked in the image. In addition to the tool-ground distance, we will experiment with showing the distance to the nearest tree and various information about individual trees, i.e., trunk size or species. One can also think about coloring the different trees differently, i.e., the trees to be cut and those that should be left alone. Tree coloring becomes especially useful for thinning operations.

B. Autonomy modules

The mission execution flow and the autonomy modules are the same as in our previous work [5] with one difference: we use behavior trees to implement the state machine.

Chassis balancing A virtual force controller is used (see [7]) to keep the machine in the desired orientation and maximize the traction. We saw that human operators controlling the machine often inadvertently break wheel contact with the ground. Losing ground contacts results in increased danger of tipping the machine over. Lastly, from our field experiments with HEAP in [5], we noticed that maximizing traction becomes very important if the ground is muddy. Note that this functionality is only possible thanks to high-performance servo valves (see Fig. 3).

Base motion planning & control All the planning modules have been ported from [5], i.e., we use the same RRT based path and approach pose planner for navigating around the environment. The machine driving is controlled using the pure pursuit controller.

Arm motion planning & control In the first step, we use the Inverse Kinematics (IK) controller to control the arm movements in operation space. IK controller is based on hierarchical optimization from [18]. The arm planner merely reaches for the trees in a straight line and keeps the arm retracted as the machine moves.

State estimation To obtain smooth and consistent state estimates, we intend to use the factor graph-based approach presented in [19]. It fuses IMU, lidar odometry, and GPS. For forestry operations, we will look into replacing GPS with visual odometry.

Tree detection At the moment, we use purely geometric tree detection from [5] however, we might extend it with visual information in the future.

Mapping & Localization As suggested in [5] we will start with using Iterative Closest Point (ICP) based localization in the pre-recorded map. The mapping system is under development at the moment.

IV. CURRENT AUTOMATION PROGRESS

We start by building a simulation environment that allows for rapid prototyping and testing to automate the machine. We use the Gazebo simulator, which is tightly integrated with ROS [20]. Almost all the functionality is implemented and tested in simulation as we are preparing the real machine for tests. This section shows a selected set of autonomy features operating in simulation.

Chassis balancing Chassis balancing in simulation is shown in Fig. 6. Harveri is asked to drive forward over the obstacles. Please note that the machine is blind and has no way of knowing the terrain. However, with the balancing controller activated, Harveri can keep all wheels in contact and the chassis leveled despite the uneven terrain.

Base motion planning & control Fig. 7 shows an example of Harveri utilizing the sampling-based planner and pure pursuit controller to navigate between the trees. The map used in these examples has been collected in a real forest, thus showcasing Harveri's ability to negotiate tight spaces in realistic situations. The pure pursuit controller used (see [5]) has been derived for vehicles with Ackermann steering and not an articulated vehicle. We expect replacing it with a controller for articulated vehicles would increase the tracking performance.

Tree detection Fig. 8 shows Harveri detecting simulated trees in Gazebo. Since the trees are well visible in the local map, this would suggest that the laser placement on the arm base (see Fig. 2c) is effective for this task.

V. CONCLUSION AND OUTLOOK

We presented Harveri, a small harvester targeted for thinning and precision harvesting. In this article, we primarily build on top of our previous work done on HEAP for the same application. So far, we have developed a simulation environment and tested components from our autonomy stack, while the hardware itself remains under development. In the near future, teleoperation remains our main goal.

Subsequently, we intend to make Harveri fully autonomous. We will focus on developing a robust localization system that can handle degenerate environments and fuse multiple sensing modalities. Furthermore, the control system needs to be modified to enable better tracking with an articulated vehicle. We could either use a different version of the pure pursuit algorithm or an optimization-based controller running in a receding horizon fashion. Lastly, Harveri needs to be extensively tested in multiple different styles of forest (e.g., clutter, floor vegetation). Harveri is still a new platform, and we most likely will have to refine sensor placement and sensor choice iteratively. Experiences gathered from Harveri automation might help us improve the machine design or even design a new platform.

Automating Harveri would help solve the labor shortage and enable more efficient forestry operations. Furthermore, forests in remote areas could be managed, and small landowners would benefit from the reduced labor cost. All together, improved efficiency could potentially help combat climate change, one of the major concerns in modern society.

REFERENCES

[1] H. C. Von Carlowitz and J. B. von Rohr, *Sylvicultura oeconomica*, 1732.

[2] H. Choudhry and G. O'Kelly. (2018) Precision forestry: A revolution in the woods. [Online]. Available: https://www.mckinsey.com/industries/paper-forest-products-and-packaging/our-insights/precision-forestry-a-revolution-in-the-woods

[3] Silvere. (2017) We know your trees. [Online]. Available: https://silvere.com/english

[4] Treeswift. (2021) Building the future of forestry. [Online]. Available: https://www.treeswift.com/

[5] E. Jelavic, D. Jud, P. Egli, and M. Hutter, "Towards autonomous robotic precision harvesting: Mapping, localization, planning and control for a legged tree harvester," *Field Robotics*, 2021.

[6] D. Jud, S. Kerscher, M. Wermelinger, E. Jelavic, P. Egli, P. Leemann, G. Hottiger, and M. Hutter, "Heap-the autonomous walking excavator," *Automation in Construction*, vol. 129, p. 103783, 2021.

[7] M. Hutter, P. Leemann, G. Hottiger, R. Figi, S. Tagmann, G. Rey, and G. Small, "Force control for active chassis balancing," *IEEE/ASME Transactions on Mechatronics*, vol. 22, no. 2, pp. 613–622, 2016.

[8] M. Hutter, P. Leemann, S. Stevsic, A. Michel, D. Jud, M. Hoepflinger, R. Siegwart, R. Figi, C. Caduff, M. Loher *et al.*, "Towards optimal force distribution for walking excavators," in *2015 international conference on advanced robotics (ICAR)*. IEEE, 2015, pp. 295–301.

[9] D. Portugal, M. E. Andrada, A. G. Araújo, M. S. Couceiro, and J. F. Ferreira, "Ros integration of an instrumented bobcat t190 for the semfire project," in *Robot Operating System (ROS)*. Springer, 2021, pp. 87–119.

[10] FPInnovations. (2020) Automated harvesting with robots in the forest. [Online]. Available: https://www.woodbusiness.ca/automated-harvesting-with-robots-in-the-forest/

[11] R. S. Lab. (2020) Heap teleoperation over 5g networks - swisscom 5g start-up challenge 2020. [Online]. Available: https://youtu.be/LV-VbmMLoik

[12] ——. (2020) Teleoperated menzi muck 545 with active chassis cleaning up a rockslide. [Online]. Available: https://youtu.be/IbMZTErlQNU

[13] F. O. for Defence Procurement armasuisse. (2020) Baptism of fire for the research demonstrator armano. [Online]. Available: https://www.ar.admin.ch/en/armasuisse-wissenschaft-und-technologie-w-t/home.detail.news.html/ar-internet/news-2020/news-w-t/feuertaufe-forschungsdemonstrator-armano.html

[14] S. Systems. (2022) Ellipse series inertial sensors. [Online]. Available: https://www.sbg-systems.com/products/ellipse-series/#ellipse-a_miniature-ahrs

[15] A. I. Systems. (2022) Mtlt335d intertial system. [Online]. Available: https://www.aceinna.com/inertial-systems/MTLT335D

[16] GEFRAN. (2022) Hall-effect single-turn rotary sensor without shaft. [Online]. Available: https://www.gefran.com/en/us/products/552-grn-hall-effect-single-turn-rotary-sensor-without-shaft?skip_redirect=true

[17] P. Fankhauser, M. Bloesch, and M. Hutter, "Probabilistic terrain mapping for mobile robots with uncertain localization," *IEEE Robotics and Automation Letters*, vol. 3, no. 4, pp. 3019–3026, 2018.

[18] C. D. Bellicoso, C. Gehring, J. Hwangbo, P. Fankhauser, and M. Hutter, "Perception-less terrain adaptation through whole body control and hierarchical optimization," in *2016 IEEE-RAS 16th International Conference on Humanoid Robots (Humanoids)*. IEEE, 2016, pp. 558–564.

[19] J. Nubert, S. Khattak, and M. Hutter, "Graph-based multi-sensor fusion for consistent localization of autonomous construction robots," *arXiv preprint arXiv:2203.01389*, 2022.

[20] N. Koenig and A. Howard, "Design and use paradigms for gazebo, an open-source multi-robot simulator," in *2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)(IEEE Cat. No. 04CH37566)*, vol. 3. IEEE, 2004, pp. 2149–2154.